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Compressed Sensing for Image Communication with various Measurement Matrices

Abstract: - This paper explores a joint method for efficient compression as well as the reliable transmission of images. In image transmission, low dormancy and very fast data transmission are the main requirements of modern wireless communications systems. Efficient and reliable image transmission through wireless networks need to handle several challenges like adverse wireless channel conditions, the need for high power consumption, man aging high computational complexity, and low error resilience capability of image compression schemes, etc. This paper deals with the compressed sensing approach in combination with *orthogonal frequency division multiplexing* (OFDM) to take care of the above challenges. There are three important steps in Compressive sensing: sparse signal representation, measurement collection, and sparse recovery. In this process, a measurement matrix is utilized to sample those elements which are significant for accurately depicting the signal in the measurement step. So, the design of precise measurement matrices is crucial for compressive sensing. This paper proposes a modified Toeplitz Diagonal measurement matrix, which significantly improves the quality of the reconstructed image with minimum data. At the same time, the use of OFDM handles multipath fading channels for reliable transmission of the image data. The simulation results also compare the performance of several measurement matrices in terms of image quality through PSNR value, the structural similarity index, and the BER for transmission performance after passing through AWGN as well as multipath channels.

Keywords: Compressive sensing, OFDM, Orthogonal matching pursuit, Reconstruction error

I. INTRODUCTION

The efficient and reliable communication of visual data plays an important role in the recent development of 5G wireless communication as well as communication through the *Internet of Things* (IoT) [4]. Currently, the Compressed sensing technique [1]–[3], [5] is being researched for efficient and reliable data transmission. In *compressed sensing* (CS), the original test image is first converted into a *discrete cosine transform* (DCT) or *discrete wavelet transform* (DWT) domain to achieve a sparsity in image data. The generated transformed domain element undergoes processing using a measurement matrix. There are several research papers available in this regard. In [6], in-depth introductions to compressive sensing techniques for images have been made. All of these schemes are based on a proper selection of measurement matrices. In [7], a random measurement matrix (Hadamard measurement matrix) has been used based on chaos scrambling to achieve compressed Sensing images; however, it gives a suboptimal performance. In [8], [9], a compressive sensing scheme is proposed based on a chaotic system. However, its reconstruction algorithm is computational complexity and the measurement matrix needed a large memory space to store the required data. To solve this problem, an optimal sparse measurement matrix has been proposed in our work with the help of a diagonal measurement matrix. The use of an optimum measurement matrix can save the bandwidth requirement by reducing the amount of data, saves storage capacity by using a sparse matrix, and also reduces the power consumption of electronic devices. However, the use of an optimal measurement matrix is not sufficient to handle the challenges raised by wireless channels and also needs an efficient technique for the reliable transmission of compressed sensing data. In this regard, some researchers have recently investigated the effectiveness of compressed information being transmitted via a wireless channel [10]. In [11], the efficacy of compression and communication via the UWB wireless channel has been examined by researchers. In [12], [13], A robust method of transmitting compressed images using OFDM, specifically designed for mobile networks, has been innovatively developed. However, this paper used the block compressed sensing method, which involves: block sparse chaotic DCT basis matrix and block chaotic DCT measurement matrix. In [14], [15], For mobile networks based on OFDM, an effective compression image transfer

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strategy was suggested that involves: Hadamard sparse basis matrix, partial DCT measurement matrix, and 16-QAM-OFDM system with visible light communication (VLC) channel. A Gaussian random measurement matrix with an M-QAM-OFDM transmission system has been used in [16]–[18] for an efficient image transmission using CS. However, among these techniques, the communication system requires high computational complexity for transmitting a huge amount of image data. So to solve this problem, We have proposed a straightforward and efficient *Toeplitz-Diagonal Matrix* (TDM) measurement matrix for the compressed sensing method. In our proposed work, a block compressed sensing technique has been used which involves DWTsparse basis matrix and Toeplitz- diagonal measurement matrix.

The TDM matrix is composed of only one primary diagonal vector which includes non-zero elements and the rest of the diagonal vectors have zero elements. The obtained TDM measurement matrix is a very simple measurement matrix that is used in the compressed sensing scheme to obtain better performance. The proposed measurement matrix has the following benefits: (1) Easy construction; (2) High detection efficiency; and (3) Fast and nearly ideal reconstructions. The outcomes of the simulation demonstrate that the reconstructed images based on the TDM matrix have better image quality compared to those produced by the Bernoulli matrix, the Gaussian random matrix, the Hadamard matrix, and even the Toeplitz matrix.

The following is a summary of the primary contributions of the manuscript.

- An efficient compressed sensing technique has been proposed based on a simple TDM measurement matrix

. • An OFDM-based compressed sensing model has been proposed for the reliable transmission of compressed images through a multipath wireless channel.

The remainder of this article is structured as follows: In Section II, we delve into OFDM and compressive sensing as applied to transmission systems. Section III showcases simulation results, focusing on evaluating both the reconstructed image quality and the performance of the proposed system in terms of *bit error rate* (BER). Finally, Section IV concludes with our findings.

II. BACKGROUND: COMPRESSED SENSING AND TRANSMISSION

1. A.Compressive Sensing

Compressive sensing, a signal-processing method introduced in 2006, focuses on reconstructing a sparse signal ψ from a limited number of linear measurements by using a suitable transform. Consider ψ as a sparse signal in the time domain with dimensions N×1. This signal x can be expressed as:

$$x=\psi X \tag{1}$$

A signal x is termed K-sparse if it contains K non-zero elements, where K is much smaller than N. If y represents an M-dimensional measurement vector, with M much less than N, it can be described as:

$$y=\phi x \tag{2}$$

Here, ϕ is an M×N measurement matrix. This matrix ϕ can be constructed using various techniques, including chaotic maps, random Gaussian matrices, or Bernoulli matrices. In this study, we used a Toeplitz-diagonal measurement matrix. For accurate recovery of x from y, two conditions must be met by the matrices ϕand ψ: (a) the incoherence condition and (b) the restricted isometry property. A Toeplitz-diagonal measurement matrix fulfills both conditions. For signal reconstruction, we used the conventional orthogonal matching pursuit (OMP) algorithm to ensure efficiency and reliability.

Proposed Toeplitz Diagonal Measurement Matrix

The Toeplitz matrix T $\in R^{M\times N}$associated with a vector t = t_1, t_2, t_3,... t_n) $\in R^N$ has entries defined as: $t_{i,j} = t_{j-i}$ Where i, = 1,2, ... ,N. This formulation signifies that the(i,j)-th entry of the Toeplitz matrix is determined by the (j i) th element of the vector t.In a Toeplitz matrix, the diagonal entries are constant, specifically $t_{i,j} = t_{i+1}, t_{j+1} \in R^N$. Therefore, the Toeplitz matrix takes the following form:

$$T = \begin{bmatrix} t_n & t_{n-1} & t_{n-1} & \cdots & t_1 \\ t_{n+1} & t_{n+1} & t_n & \cdots & t_2 \\ & & & & \vdots \\ t_{n+2} & t_{n+3} & \cdots & \cdots & \\ t_{2n-1} & t_{2n-2} & t_{2n-3} & \cdots & t_n \end{bmatrix}$$

We randomly choose a subset S ⊂ (1, ..., N) of cardinality M ≪ N, the Restricted Isometry Constant of the Toeplitz $\delta_k \ll \delta$ is obtained with a high probability:$N \geq C\delta K^2 \log\frac{N}{K}$Where K is the sparsity of the signal and N is its length. In compressed sensing, the Toeplitz matrix reconstructs the signals very well. But because it is as dense as the Gauss or Bernoulli matrices, it takes up a lot of storage space and has a high time cost. The Toeplitz matrix also makes it difficult to implement and advertise hardware. Then, Florian Sebert proposed the block diagonal Toeplitz matrix (BDTM) [20], [21], The Block Diagonal Toeplitz Matrix (BDTM) offers advantages such as reduced storage space, faster processing time, and simplified hardware implementation. However, its performance is constrained by the requirement that matrix elements adhere to the pattern Tij = tj−i,limiting its effectiveness.To address these limitations, we propose a novel measurement matrix called the Toeplitz-Diagonal Matrix (TDM). The TDM is derived from the Toeplitz matrix by retaining only the elements along a diagonal line and setting them to ’1’. The construction of the TDM is illustrated in equation (4). Unlike the BDTM, the TDM imposes no restrictions on matrix dimensionality. Furthermore, the TDM takes into account the energy distribution of an image, resulting in a sparser representation and facilitating hardware implementation.

$$\phi_{ij} = \begin{cases} 1 & \\ 1 & \textbf{For} \quad \textbf{i=1or} \\ o & \text{Otherwise} \end{cases} \tag{3}$$

Where $\phi_{i,j} \in R^{M\times N}$, $i \in (1, M), j \in (1, N)$. This is the proposed TDM measurement matrix.

$$\phi= \begin{bmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \ddots & 0 \end{bmatrix}$$

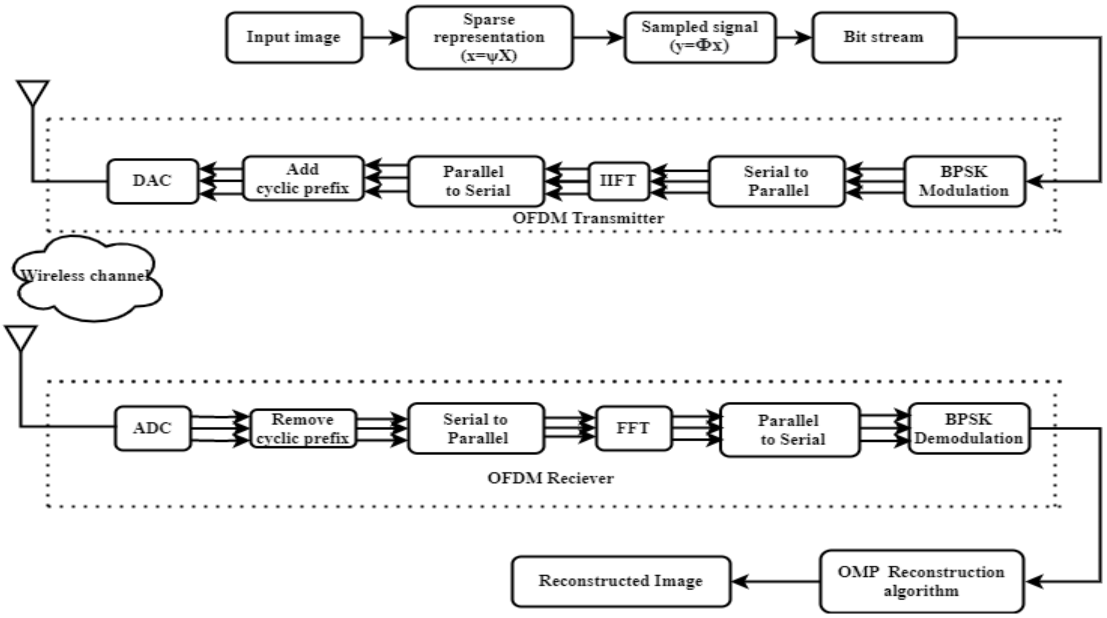

Fig. 1. Flow chart of the proposed method.

B. Compressed transmission model

The combination of compressed sensing and transmission system using a wireless channel is depicted in Fig. 1. The compressed data is first encoded into a binary bit stream on the transmitter side. This bit stream is modulated by binary phase shift keying modulation with the dimension N and denoted by a signal vector $s = s_0 \; s_1 ... \; s_{(N-1)}$. Then, the resulting data is sent to the IFFT section. Here data is converted into a frequency domain to a time domain signal. This process follows the below equation.

$$x = G^H X \qquad (4)$$

where G is a discrete Fourier transform (DFT) matrix, and it has (m, n) element which is introduced by the below equation.

$$G(m,n)=\frac{1}{\sqrt{N}} - e^{\frac{2\Pi mn}{N}} \qquad (5)$$

The obtained time domain OFDM signal is $x = x_0\, x_1 . . . x_{(N-1)}$ .After that, a cyclic prefix is introduced to avoid interference between symbols. After that, the signal goes via the power amplifier before being transmitted over the channel. When the acquired signal's cyclic prefix is eliminated from the side of the receiver, the noisy signal can be represented as

$$k = l.x + w \qquad (6)$$

In this scenario, $l = [l_0, l_1, . . . , l_{(L-1)}]$ represents the discrete impulse response of the wireless frequency selective channel, while $w = [w_0, w_1, . . . , w_{(N-1)}]$ denotes the additive white Gaussian noise (AWGN). The process involves convert- ing the decoded Binary Phase Shift Keying (BPSK) symbol stream into a bit stream, followed by inverse quantization processing. The resulting real numbers are then recovered using the Orthogonal Matching Pursuit (OMP) algorithm. Subsequently, this data is utilized as image data, and the images are reconstructed. Finally, the performance of the proposed CS-OFDM systems can be analyzed by examining the PSNR and BER.

III. RESULTS AND ANALYSIS

In this section, various inspections are evaluated for testing the performance of the proposed CS-OFDM scheme. In our inspection, several test images such as Lena, Cameraman, peppers, and boat images have been used. The test image is first converted into a sparse signal on a DWT sparse basis. The obtained sparse signal is measured by an improved Toeplitz

-Diagonal measurement matrix.To ensure a balanced comparison, we utilized the conventional OMP reconstruction algorithm within the CS framework. Various performance evaluation scenarios are outlined as follows.

- *PSNR Performance*

In this subsection, we examined Compressive Sensing per- formance, by using our improved Toeplitz-Diagonal measure- ment matrix. Mean Square Error (MSE) and Peak Signal-to- Noise Ratio (PSNR) serve as evaluation metrics for assessing the quality of the reconstructed image. These metrics exhibit an inverse relationship: as one decreases, the other increases. A lower MSE signifies a smaller disparity between the original and reconstructed images [17], [19] and shows better PSNR. Scenario 1: The PSNR effectiveness of our proposed com- pressive sensing (CS) method was evaluated across different compression ratios using ”Lena” and ”Cameraman” as test images. The experiment focused on assessing the effective- ness of CS-OFDM based on image quality measured by PSNR. The CS method employed DWT sparse basis and an improved Toeplitz-Diagonal measurement matrix, along with four types of conventional measurement matrices: partial chaotic Hadamard matrix, Gaussian measurement matrix,Bernoulli matrix, and Toeplitz measurement matrix.Simulation results for the ”Lena” and ”Cameraman” images, each with a size of 256 256, are presented in Fig.2.

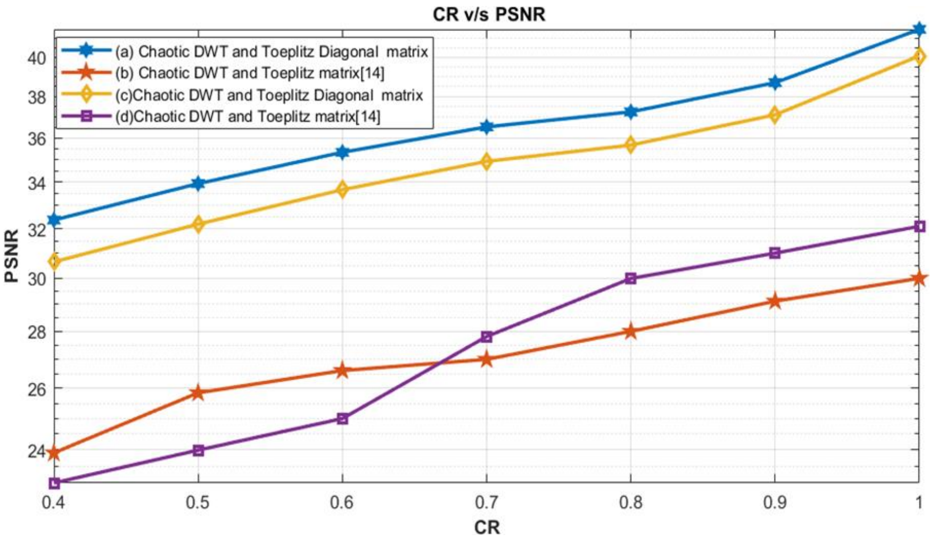

Fig. 2. Comparison of the reconstruction accuracy performance of the 256 x 256 images ”Lena” and ”cameraman.”

Analysis of these results, along with data from Tables I and II, indicates that the CS scheme utilizing our improved Toeplitz-Diagonal measurement matrix yields superior quality in the reconstructed images compared to the other CS schemes. scenario 2: This study investigates how varying the number of sub blocks of images impacts the Peak Signal-to-Noise Ratio (PSNR) when using the combined chaotic Discrete Wavelet Transform (DWT) sparse basis with the Toeplitz- Diagonal Matrix (TDM) measurement matrix, all at the same compression ratio (CR) of 3/4. The 2 input images are used for evaluating the performance of our proposed TDM measurement matrix. All test images are partitioned into subblock sizes of 32 × 32, 64 × 64,128 × 128, and 256 ×256. All blocks are sampled using the same CS scheme. Table III shows how the size of the image’s sub-block affects CS algorithms’ performance in terms of PSNR. In the simulation experiment, the test image utilized is Lena, sized at 512 × 512 pixels.

Fig. 3. Reconstructed images with Toeplitz -Diagonal measurement matrix: (1) Reconstructed test images with 256 × 256 ;(2) Reconstructed test images with the size of 512 × 512.

Each sub-block of the image is compressed at a compression ratio of 3/4. then we obtained the maximum PSNR of 42.0272 dB with the size of the sub-block of 256 × 256. We also observe that the value of the PSNR significantly rises with increasing sub-block size.Fig.3 shows the visual performance of the reconstructed images using a TDM measurement matrix with compressed sensing for data transmission in wireless networks. In this figure, we used 4 test images: Lena, Peppers,Cameraman and Boats with sizes 256 × 256 and 512 × 512. In this situation, the sampling rate of each subblock is set as 3/4 and the dimension of each subblock is 32 × 32. From this figure, we got the better-reconstructed image quality with the dimension of 512 × 512 as compared to the dimension of 256 × 256.scenario 3:The performance of CS methods' PSNR, which are based on DWT sparse basis and TDM measurement matrix, are affected by various compression ratios. The reliability of the reconstructed images using Compressed sensing methods is shown in Fig. 3. The Peak to signal-noise ratio is improved with increasing *compression ratio*(CR) of the Compressed Sensing scheme.

- *Differential Attack Analysis*

A differential attacker is a type of adversary in the context of image reconstruction. It aims to exploit the vulnerabilities in the reconstruction scheme by analyzing the differences between two versions of the same image, typically an original image and a reconstructed image. The attacker tries to deduce information about the reconstruction process by analyzing the changes in the pixel values between the two images.This type of attack is known as a "differential attack." It typically assesses resistance to such attacks using measures like NPCR (*number of pixels change rate*) and UACI (*unified average changing intensity*).NPCR and UACI are two commonly used parameters to measure the resistance of a reconstruction scheme against differential attacks.They are commonly used parameters to measure the percentage of pixels that differ between the original and reconstruction images. It provides an indication of the change introduced by the reconstruction process.

TABLE COMPARISON OF THE EFFICACY OF RECONSTRUCTION QUALITY FOR THE 256 X 256 "LENA" IMAGE. THE VARIOUS MEASUREMENT MATRICES INCLUDE BERNOULLI, CHAOTIC HADAMARD MATRIX, GAUSSIAN, ANDTOEPLITZ MATRICES IN ADDITION TO THE DWT SPARSE MATRICES

CR	Gaussian matrix	Teoplitz matrix	Bernoulli matrix	Hadamard matrix	**TDM**
0.4	14.7946	18.9499	14.9659	22.2918	**27.4498**
0.45	15.5193	23.1077	15.7132	23.3706	**28.7456**
0.5	16.219	23.7476	16.233	24.5063	**29.9758**
0.6	17.8772	26.5202	17.8727	26.464	**29.9758**
0.7	19.72	28.4983	20.0042	28.9744	**31.4228**
0.75	20.9321	29.3909	21.2764	29.848	**32.0618**

TABLE II
COMPARISON OF THE RECONSTRUCTION QUALITY EFFICIENCY OF THE 256 X 256 "CAMERAMAN" IMAGE. THE VARIOUS MEASUREMENT MATRICES INCLUDE BERNOULLI, CHAOTIC HADAMARD MATRICES, GAUSSIAN, AND TOEPLITZ MATRICES IN ADDITION TO THE DWT SPARSE MATRICES.

CR	Gaussian matrix	Teoplitz matrix	Bernoulli matrix	Hadamard matrix	**TDM (Proposed)**
Complexity	(MN)	(MN(N+1))	(MN(N+1))	(MN(N+1))	(MN)

0.4	21.7186	21.3819	215866	22.8577	**28.889**
0.45	22.6521	23.689	23.2407	23.4885	**29.958**
0.5	23.654	23.8678	23.9196	24.1996	**31.121**
0.6	25.9971	26.4245	25.5671	26.7476	**31.324**
0.7	28.1521	28.3856	28.2249	29.5014	**33.023**
0.75	29.4331	30.0693	30.1553	31.0771	**33.416**

TABLE III
EFFECT OF THE BLOCK SIZE ON THE PSNR (DB) PERFORMANCE (INPUT:LENA IMAGE WITH 256 × 256 SIZES

Measurement matrices	32 × 32	64 × 64	128 × 128	256 × 256
TDM (Proposed)	**25.0709**	**25.4645**	**37.2816**	**42.0272**
Toeplitz matrix[Ref.13]	27.4411	26.7588	26.7343	26.8927
partial Chaotic DCT matrix[Ref.13]	27.6487	28.3950	28.3330	28.2816

The higher the NPCR value, the more effective the scheme is in altering the pixel values. A higher NPCR value, closer to 100%, indicates a higher level of pixel alteration and suggests a better resistance against differential attacks.UACI (Unified Average Changing Intensity) measures the average difference in intensity between corresponding pixels in the original and reconstruction images. It quantifies the average impact of the reconstruction process on the pixel values.UACI is typically reported as a value between 0 and 1. A lower UACI value suggests a smaller average change in pixel intensity and indicates a better resistance against differential attacks [16].

TABLE IV PERFORMANCE OF LENA IMAGE ON THE PSNR, MSE, NPCR, UACI,AND THE SSIM.

CR	PSNR	MSE	NPCR	UACI	SSIM
0.4	31.3795	16.6934	0.8743	0.0170	0.8908
0.45	32.3633	13.9087	0.8610	0.0151	0.9058
0.5	33.9322	11.1459	0.8457	0.0130	0.9229
0.6	35.3427	8.2464	0.8160	0.0108	0.9403
0.7	36.5306	6.3169	0.7841	0.0091	0.9524

TABLE V
SIMULATION SYSTEM PARAMETERS

Sl. No.	**Simulation**	**Parameters**
1	Delay Taps	2
2	n Taps	2
3	Modulation	BPSK
4	Ncp	2
5	Channel	Rayleigh fading, AWGN

TABLE VI
PERFORMANCE OF THE CAMERAMAN IMAGE ON THE PSNR, AND THE RUNNING TIME WITH TOEPLITZ -DIAGONAL MEASUREMENT MATRIX

Diagonal element	192	162	132	102	72	42
PSNR(dB)	33.3664	31.9828	31.1007	28.8732	26.6309	24.1360
TIME(s)	9.077	8.182	7.494	6.485	5.541	4.867

NPCR and UACI metrics are computed on various test images and the results are tabulated in Table IV with different compression ratios. In Table 4, we find the NPCR and UACI decrease which increases the compression ratio.Table IV, demonstrates the different results of our mea- surement matrices based on various characteristics namely PSNR, MSE, NPCR, UACI, and *structural similarity index measure* (SSIM) [16] of the different reconstructed images. Here the PSNR performance of our modified measurement matrix increases as increases the compression ratio as the conventional result and we find the acceptable PSNR 31.3795dB performance with high compression at CR is 0.4 for the Lena image. Also, the MSE results of different images are also listed in Table.

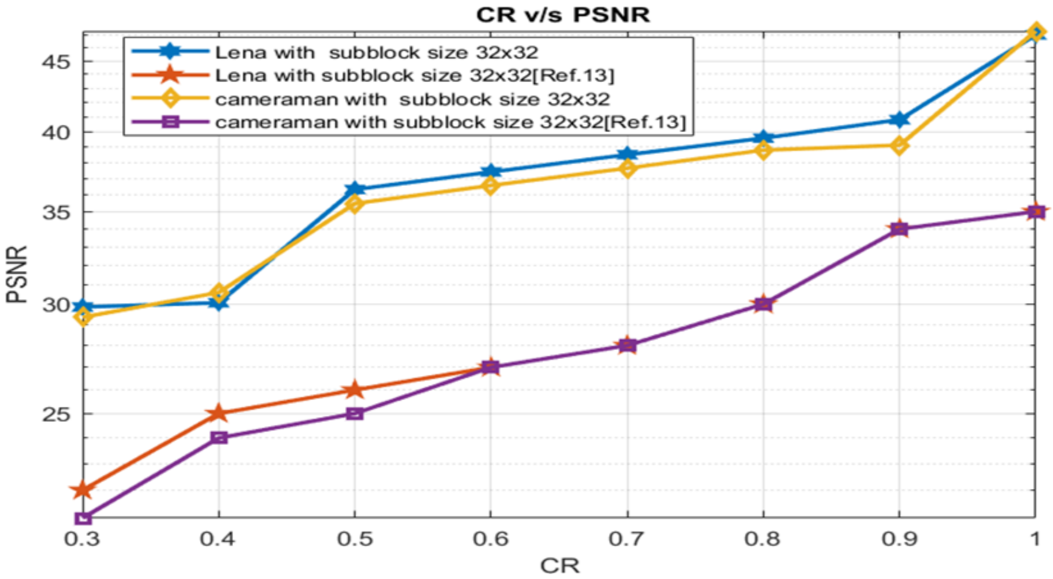

Fig. 4. The reconstruction Peak Signal-to-Noise Ratio (PSNR) performance of images with sub-block sizes of 32 × 32 for both Lena and Cameraman images, each sized at 512 × 512 pixels, is evaluated.

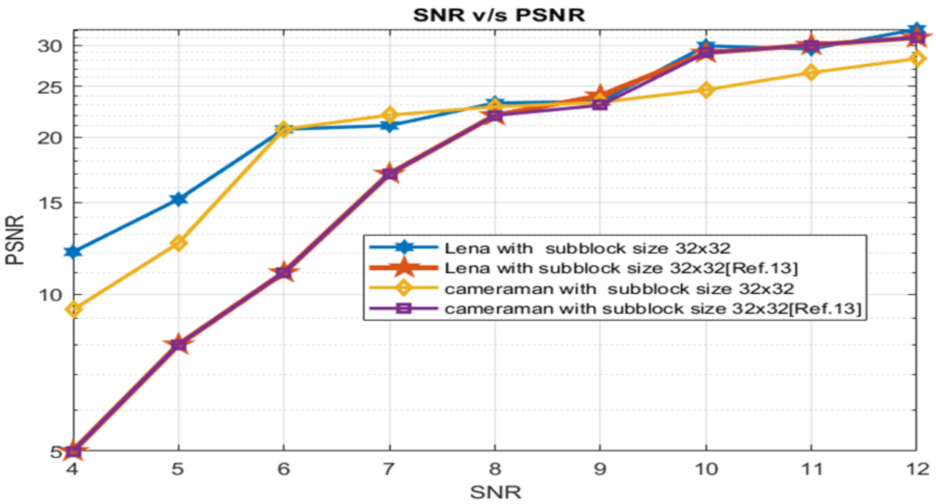

Fig. 5. PSNR performance comparison over the AWGN channel.

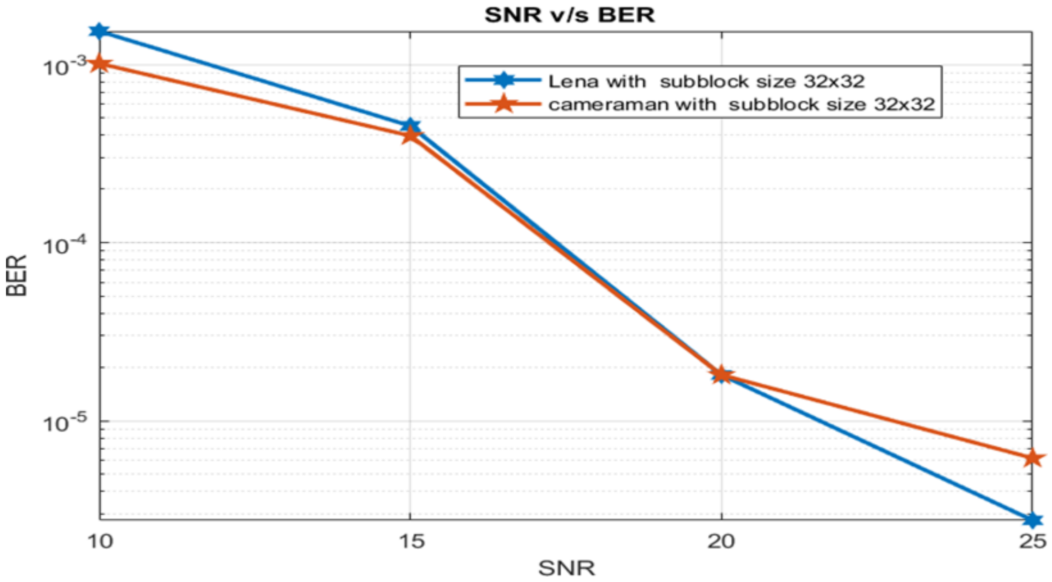

Fig. 6. BER performance comparison over the multipath fading channel.

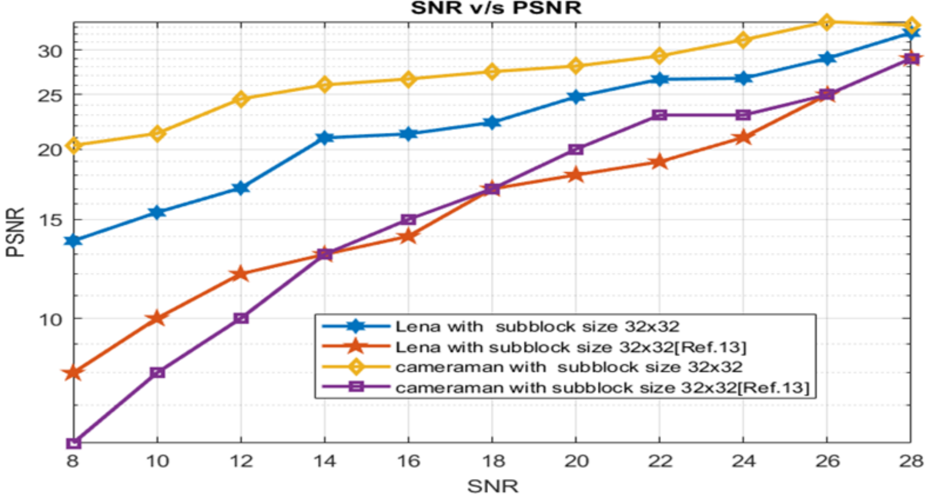

Fig. 7. PSNR performance comparison over the multipath fading channel.

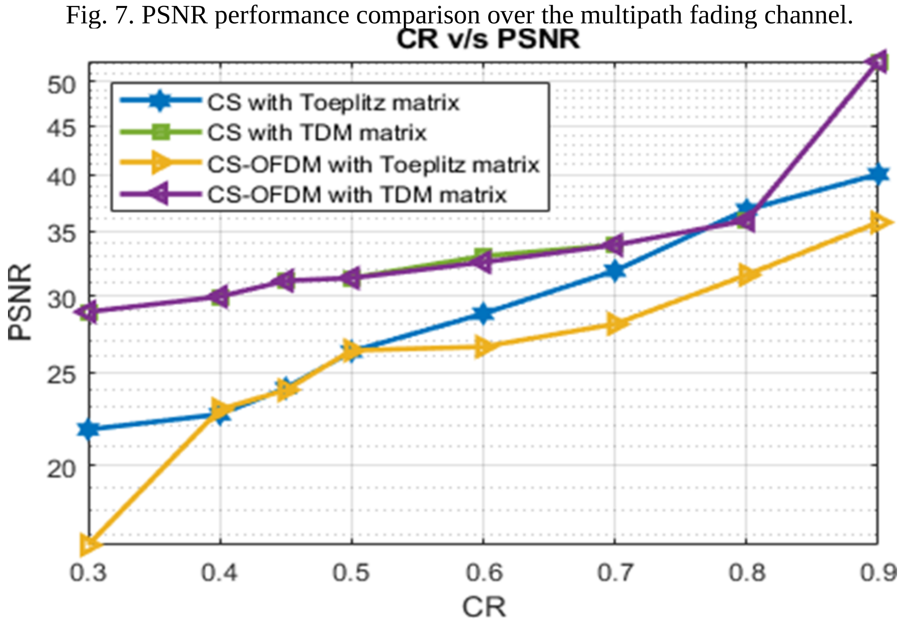

Fig. 8. Reconstruction accuracy performance comparison of Teoplitz matrix, TDM matrix, CS-OFDM with Teoplitz matrix, CS-OFDM with TDM Matrix by using cameraman test image with the size of 256 × 256 over the multipath fading channel.

- *Analysis of transmission performance with sub-block size of the test image.*

In this subsection, the performance of the two-step BPSK- OFDM system is examined as per the 802.11a standards. The OFDM scheme consists of a CS method. The main simulation parameters can be summarized in Table V. The input images are Cameraman and Lena, both of which are 512 x 512 pixels in size. We examine a CS-OFDM system's BER performance over the AWGN channel. In the following experiment, after sampling the actual image with our suggested CS, the generated data is changed into BPSK symbols, which is a chaotic sequence. Next, By using IFFT modulation, the BPSK signal is processed, and OFDM signals are produced and sent into the wireless channel. And at the receiver, the image is reconstructed by the OMP algorithm.Fig. 4 show reconstruction PSNR performance of images with the sizes of the sub-block of 32 × 32 for Lena and Cameraman images with the size of 512 × 512.From this figure we got better performance as per given reference. Fig. 5 presented the quality of the reconstructed images in terms of PSNR based on the AWGN channel. As can be seen, a sub- block size of 32 × 32 performs better in terms of PSNR when the SNR is under 10 dB. The Bit Error Rate performance for the CS-OFDM scheme over the multipath fading channel is shown in Fig. 6.here every sub-block of the test image is fixed 32 × 32 and the compression ratio is fixed 3/4. The Bit Error Rate results of the sub-block size of 32 × 32 are nearly the same for both images. Therefore, the size of the image's sub- block has a negligible impact on the BER performance. Fig. 7 presented the quality of the reconstructed images in terms of PSNR over the multi-path fading channel for the CS-OFDM scheme. We can see that the PSNR (in the case when the sub- block is of size 32 × 32 pixels) of the image is increasing with increasing the SNR for the two test images.Figure 8 illustrates the performance of the CS-OFDM system utilizing DWT sparse basis and TDM measurement matrices, extensively examined in this study. We conducted a comparative analysis between the employed measurement matrix and other existing matrices, as detailed in our conference paper [19]. Notably, our TDM measurement matrices exhibited superior PSNR performance compared to the Toeplitz matrix. Furthermore, when the compressed signal was subjected to a channel with SNR 10 dB, we observed enhanced performance with our TDM measurement matrix. This improvement was consistent even without passing the signal through the channel using the same measurement matrix. Conversely, the Toeplitz matrix yielded the poorest results, both with and without passing through the channel.

IV. CONCLUSION

In this paper, we have presented a new CS-OFDM model for communicating the compressed images based on a mod- ified Toeplitz -Diagonal measurement matrix in compressed sensing. In this process, the image is compressively sampled using DWT sparse basis and Toeplitz -Diagonal measurement matrix. The performance is evaluated based on BER, NPCR, UACI, SSIM, and PSNR of several reconstructed images in this paper. The simulation results show the performances are improved significantly in terms of reconstructed image quality and computational complexity. This work can be further ex- tended for optimizing the statistical aspects of the compressed image data to enhance communication performance.

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